Intelligent Temporal Data Driven World Actuation in Ambient Environments

Case Study: Anomaly Recognition and Assistance Provision in Smart Home

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Abstract — A possible resident of smart home is an old person or an Alzheimer patient that should be assisted continuously for the rest of his life; however, normally this person desires to live independently at home. Typically, this person may forget sometimes completion of the activities; may realize the activities of daily living incorrectly, and may enter to dangerous states. In this context smart home project is proposed as an ambient intelligent environment, in which on one hand the resident is observed continuously through the embedded sensors, and on the other hand the resident is assisted automatically through the embedded electronically controllable actuators. In this work, we propose an approach to interpret the sensors' observations and how to automatically reason in the required assistance. The result is provision of automated assistance for the smart home resident.

I. Introduction

Activity recognition field of research deals with observation of the activities in ambient environments in order to model and recognize the activities. Activities of Daily Living (ADLs) [4] are surveyed in the Smart Home, which is a home-similar ambient environment that observes the activities of the resident through some embedded sensors. These observations are converted to data and by application of the artificial intelligence techniques are analyzed. The result of the data analysis in smart home is the provision of information that helps to achieve the smart home design objectives. Assisting the people to accomplish the ADLs, increasing the quality of life, and optimizing the spent energy at home are some of the objectives in smart home design. In this context, activity recognition is justified as a key point in information provision at smart home to achieve the objectives on behind of smart home design [5].

A. Introduction to assistance provision process

Provision of assistance in smart home is a difficult and sophisticated task. There are several reasons that made this problem as a keyhole in smart home laboratories; therefore, although many researches about the activity recognition in smart home are proposed, the ultimate objective of smart home design, which is the assistance provision, was not well dealt with. One reason is that in most of the proposed activity approaches the *correct realization* of activities is not considered and they suffice to make probabilistic predictions in smart home [10]; however, technically, this problem depends on many variables, so it is difficult to be modeled. On one hand the reasoning system of the smart home should know what the main actual need of smart home resident is and on the other hand the consequences of the smart home reaction to this requisite should be taken in to account.

Our proposed approach on assistance provision follows three major steps. At first, it calculates what is expected from the world to be, then it discovers the anomaly and at the third step it selects the best reaction to the discovered anomaly. The required knowledge of the first step is provided from the activity recognition process [10] and in this paper, we would discuss the second and third steps. In fact, we would intend to propose a practical application of the work proposed in [10].

B. Anomaly Recognition

In order to recognize the anomalies, the Anomalies Recognition and Assistance Provision Reasoning System (ARAPRS) should distinguish the normal states from the abnormal states. It should justify the observations by finding explanation(s) for them. If there is anomaly, it should calculate what is missed. In the next step, the ARAPRS should reason what is the best reaction to the discovered anomaly. The ultimate goal of the ARAPRS is to return the world to normal state. Therefore, it can be inferred that deviation from the normal state and recognition of anomaly are the basic reasons of the world actuation for assistance provision.

C. System viewpoint on the assistance provision

Generally, the process of knowledge provision, inference making and reasoning can be performed in two strategic ways. The first strategy is to transfer the needed knowledge from an expert mind to a system; however, the second strategy proposes to train an intelligent system with normal world states (smart home observations), so that many detailed information about activities could be included in the training data. Considering activity recognition is a type of NP-hard problems, so it would be a difficult task for the expert to train well the system. The proposed solution is a type of intelligent data understanding method, which gives a systematic viewpoint on the activity recognition and the assistance provision problem in smart home (see figure 1).

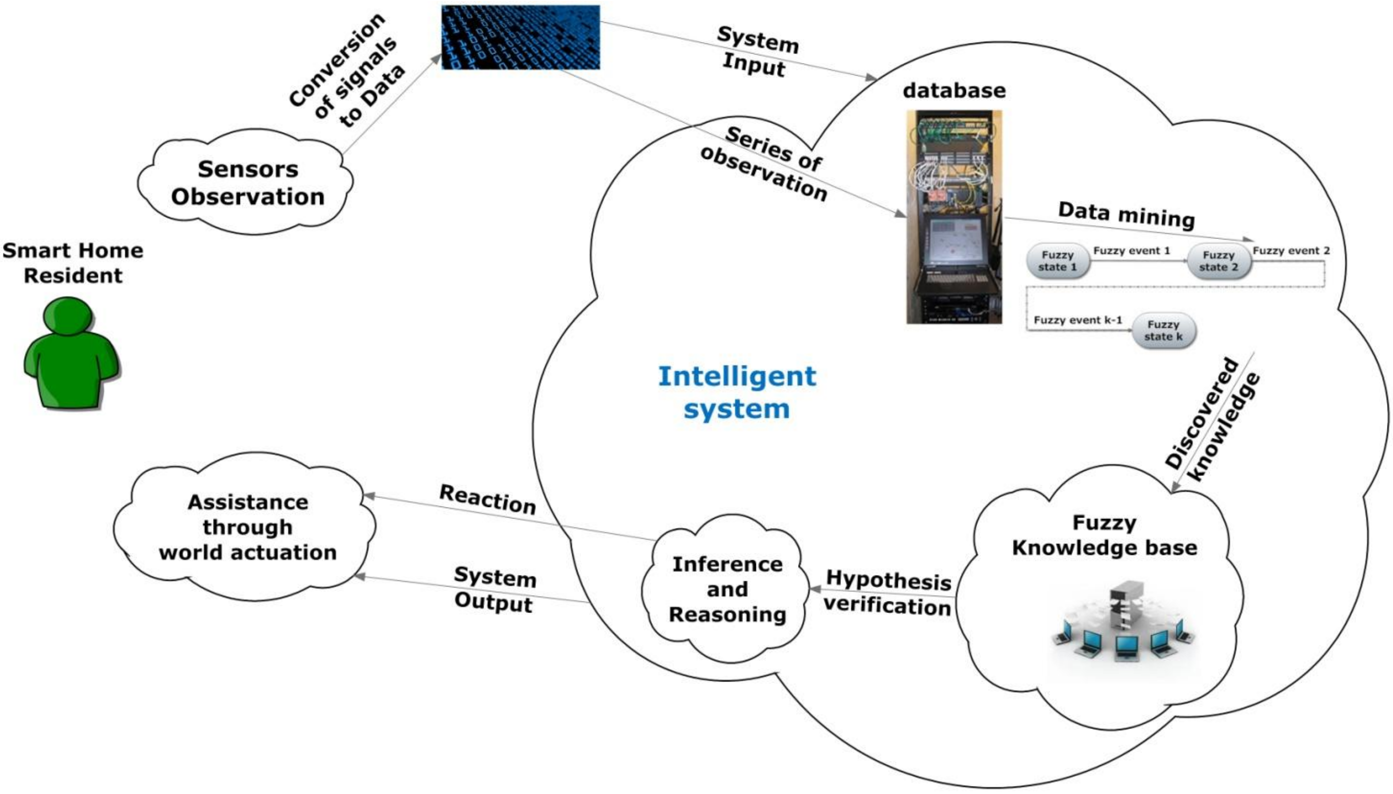

Fig. 1. System viewpoint on the activity recognition and assistance provision

We select the (intelligent) system view point on the assistance provision problem; because we can divide the smart home ambient environment into two major groups of the system intern and system extern. The system collaborates to its environment by inputting data and outputting world actuation. Further explanation is that we consider the smart home as an activity observer and this data indicates the behavior of an intelligent system. "Normal world state" is the final goal of this system and the system tries to achieve this final goal through world actuation. Therefore, smart home is a big data warehouse that contains the intelligent system's behavior and using data mining techniques the behavior of this system can be modeled [2]. It predicts the future events that will happen and moreover provides information about the resident intention in order to assist the resident (rational agent) [9].

D. Introduction to the contributions

In this work, we would contribute to the artificial intelligence by proposing a fuzzy temporal data-driven approach that verifies correct realization of activities. Moreover, we would propose a new fuzzy operator and we call it "fuzzy symmetriser". The important exclusivity of this work is proposal of a data-driven strategy for assistance provision and anomaly recognition, which permits to give automatic assistance in ambient environments.

II. PRIMARY KNOWLEDGE PROVISION

In [10], we proposed a fuzzy conceptual structure per each activity and we drew a hierarchy of concepts in smart home. In this concept hierarchy, the observations (raw data) form the lowest level of the hierarchy and possible inferences (hypotheses) that may justify the observations are the higher level concepts that make a higher level of this hierarchy. This concept inference can be continued and higher levels of concepts can be formed. The highest level concept is the Normal World Generic Function (NWGF) which at a glance describes how a normal world could be (see figure 2). Applying this information, the ARAPRS distinguishes the normal states from the abnormal states.

Fig. 2. Hierarchies of concepts in smart home [10]

Applying this information hierarchy, ARAPRS may calculate and design an objective function for realization of a series of recovery actions or a recovery activity in order to return the world to the normal state. In continue of this paper we would focus on the ways this knowledge is applied.

III. ANOMALY RECOGNITION PROCESS

As it was mentioned earlier, the ARAPRS would require patterns that according to them, it could distinguish the normality of world state. In the proposed ARAPRS, we applied an extension of fuzzy logic [1] in order to calculate the similarity degrees to the normal states and dissimilarity degrees to the abnormal states, and then it is used as criteria for reasoning. In order to form the required knowledge for ARAPRS, the information provided by the activity recognition process is taken as the input. A problem with this knowledge is that it does not indicate what the "abnormal" is. In other words, this knowledge says what state is more similar to the normal state, but it doesn't indicate a criterion for being abnormal. In order to provide the abnormality criteria, the *imaginary* concepts representing opposite of the normal concepts are calculated and formed. These opposite concepts would represent the abnormal states. The main idea behind this process is that the possible abnormal world states are states that are relatively the farthest concepts to the normal states. The more an observation is similar to a normal concept the more it is far from its opposite concept then the observation is in a normal state. In contrast, the more observation is similar to an abnormal concept the more it is far from a normal concept, so the observation is in an abnormal state. The result is that knowing the entire possible normal world states we can calculate patterns that distinguish well both the normal and abnormal states.

A. Fuzzy Symmetriser Operator

Fuzzy Symmetriser Operator (FSO) is proposed as an operator that is performed on the fuzzy numbers and based on the available knowledge it calculates the symmetric qualities of the inputted concepts. This proposed operator applies "fuzzy not operator" on each attribute of the fuzzy multi-attribute objects in order to calculate the symmetry of the fuzzy concepts.

Proposition1. Absolute Fuzzy Symmetriser Operator (AFSO): considering the set 'W' contains concepts that each of them has 'n' fuzzy attributes ($\tilde{r}_i \in \tilde{R}_i$), then the symmetry of the $\{w(\tilde{r}_1, \tilde{r}_2, ..., \tilde{r}_i, ..., \tilde{r}_n) \mid w \in W, \tilde{r}_i \in \tilde{R}_i\}$ would be calculated by performing the "fuzzy not" operator on each attribute:

$$AFSO(w(\tilde{r}_1, \tilde{r}_2, ..., \tilde{r}_i, ..., \tilde{r}_n)) = w'(1-\tilde{r}_1, 1-\tilde{r}_2, ..., 1-\tilde{r}_i, ..., 1-\tilde{r}_n)$$

The symmetriser criterion (the concept that all of the concepts are symmetrised around it) is the concept which has the maximum similarity degree to all of the existing concepts. In other words, it is the cluster center of the set 'W'. In order to calculate the cluster centers please refer to [6].

Example1. Analyzing 10 observations from a world attribute (reported in table1), the cluster center of these observations is discovered applying subtractive clustering method [3] at the Influence Range of IR=2.

TABLE I. TEN TEMPORAL OBSERVATIONS FROM A WORLD ATTRIBUTE

Time of Observations	Value	Normalized Time	Normalized Value	AFSO(Time)	AFSO(Value)
1	12	0.0510	0.2472	0.9490	0.7528
2	17	0.1019	0.3502	0.8981	0.6498
3	14	0.1529	0.2884	0.8471	0.7116
4	17	0.2039	0.3502	0.7961	0.6498
5	20	0.2548	0.4120	0.7452	0.5880
6	10	0.3058	0.2060	0.6942	0.7940
7	13	0.3568	0.2678	0.6432	0.7322
8	15	0.4077	0.3090	0.5923	0.6910
9	16	0.4587	0.3296	0.5413	0.6704
10	17	0.5096	0.3502	0.4904	0.6498

In table 1, we have illustrated that the tenth observation is the cluster center of the mentioned observations. In figure 3, we have illustrated how concepts are symmetrised around the mentioned cluster center.

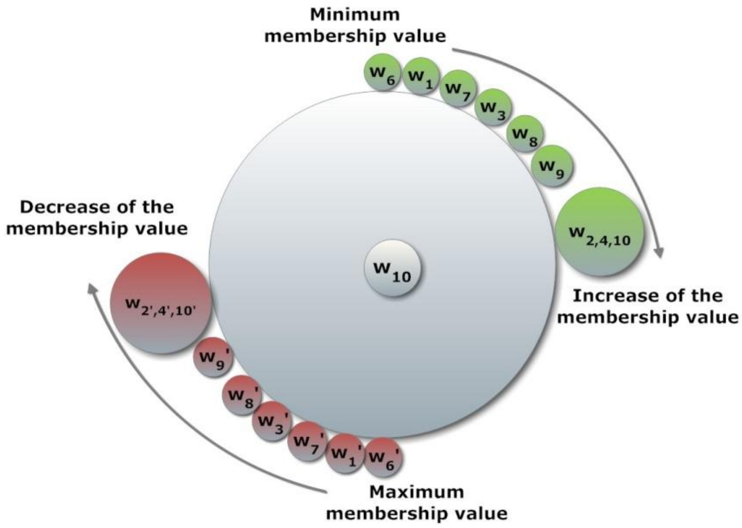

Fig. 3. Symmetrising the learned concepts (indicated in table 1) around the tenth observation

In figure3, we have illustrated that the learned concepts from a system behavior can be symmetrised and the normal states can be well distinguished from the abnormal world qualities. The abnormal states are colored with red and the normal states are colored with green. The tenth observation of this dataset is the most similar concept to the both normal and abnormal world state definitions.

B. Anomaly recognition reasoning system

In this section, we present the methodology of anomaly recognition and the way it is implemented.

1) Reasoning

The strategy to recognize the world state normality is estimation of the *similarity degree* between live observations and the models of known normal states. In fact, in order to recognize the anomalies we would measure, how much the live observations are closed to the normal states and how much they are far from the abnormal world states. Therefore, the distance of an observation to a normal world description versus the distance to an abnormal world description is the criterion for anomaly recognition.

2) Implementation applying Support Vector Machines

Support Vector Machine (SVM) is a learning model, which is used for inference making [6]. It takes a set of input data (training observations) and predicts, for each given input (live observations), which possible classes form what outputs (normal or abnormal world state). Given a set of training data (knowledge presented in figure 3), each marked as belonging to one of the normal or abnormal world states (in figure 3, marked by green or red color), an SVM training algorithm builds a structure that assigns live observations into normal or abnormal world state categories. An SVM structure is a representation of the training data as the mapped points in space, so that the observations of normal and abnormal world states be divided by a clear gap, which is as wide as possible (see figure 9). Live observations are then mapped into the same space and predicted to belong to one of the categories based on which side of the gap they fall on.

Several methods such as Fuzzy Inference System (FIS) [2], C4.5 [9] or k-nearest algorithm [6] can be applied to estimate the similarity degree discussed in the latter section; however, we prefer to apply the SVM. The reason of this selection is that generally, SVM in most of the researches demonstrates more precise results, because it performs internally an optimization process on the structure that it makes [6]. The second reason is that we can directly train it with the fuzzy cluster centers (calculated from the fuzzy clustering process) and therefore it decreases the process complexity for us.

3) Training data

In this section, we discuss how to calculate the training data of anomaly recognition system. Anomalies can occur at every level of concept (see figure 2) and we propose to perform anomaly recognition per each level of concept. The deeper level is selected, the more details about activities are paid attention, and generally the more sensitivity on standard learned form of activity realization is put. If we desire to verify multiple levels of anomalies then we can imagine a typical symmetric fuzzy system such as what we illustrate in figure 4.

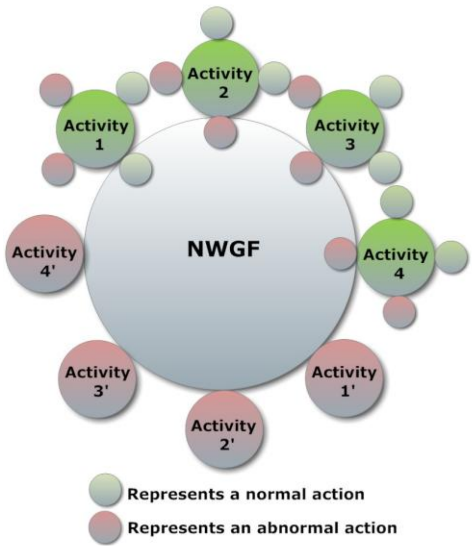

Fig. 4. Symmetrising concepts in different levels

In figure 4, it is presented that not only details such as simple actions can be symmetrised, but also more complicated concepts such as activities may be symmetrised too. Per each concept many criteria can be found in order to find its symmetry, because we may discover several cluster centers when more details in the fuzzy conceptual structures of the activities are desired, so per each cluster center we can symmetrise the concepts. Therefore, the ultimate fuzzy conceptual structure of the reasoning system can hold its symmetric schema.

In order to perform anomaly recognition, we propose to do it per each concept level by a top-down strategy. For example, considering the knowledge that we discovered in [10], at first, we begin with verification of the NWGF, if the world generally seems to be normal then correct realization of the activities are verified. In the case that anomaly is recognized it arrives the time to perform world actuation in order to return the world state to the normal state. The process of world actuation and assistance provision is the subject of the following section.

IV. ASSISTANCE PROVISION PROCESS

Recognition of the anomalies is not sufficient in smart home and the intelligent system should react in real-time to the recognized anomalies in order to return the home state to the normal state and selection of the best reaction to the anomaly is the main subject of this section.

Reaction of the intelligent systems such as smart home depends at first to the available facilities and embedded actuators. This is as well as the dependency of a smart home recognition power on the observatory facilities. We can imagine a day that robots actuate the world by realizing the automated activities; however, up to now we have not seen any work representing robotic-based approach for assistance provision in smart home. Although, we do not intend mainly to represent a robotic-based approach for assistance provision, we hope that the proposed idea in this section be helpful for future researchers who will work in this area. For now, in smart home project, it is presumed that already there is a resident which can accomplish the activities, plans and actions for return of the home state to the normal state. Therefore, technically this problem can be mapped to selection and play of the best previously-provided movie for the smart home resident in order to guide him correct his behavior. In other words, the role of the actuators is to guide the resident to perform the appropriate recovery activities.

A. Fuzzy Symmetriser Operator for assistance provision

Similar to what we performed in anomaly recognition stage, for the assistance provision we would try to make a symmetric fuzzy conceptual structure, but in this step we do not take the imaginary opposite concepts into account. Here, we put each normal concept in front of other normal real concepts. By this way, we would calculate realization of what known action or activity may return the smart home to the normal state.

Proposition2. Relative Fuzzy Symmetriser Operator (RFSO): considering the set ‘W’ contains concepts that each of them has 'n' fuzzy attributes ($\tilde{r}_i \in \tilde{R}_i$) and r^* is the fuzzy cluster center of the $\tilde{R}_i$, then the symmetry of the $\{w(\tilde{r}_1, \tilde{r}_2, ..., \tilde{r}_i, ..., \tilde{r}_n) \mid w \in W, \tilde{r}_i \in \tilde{R}_i\}$ would be calculated by performing the "fuzzy extraction" operator on each attribute:

$$RFSO(w(\tilde{r}_1, \tilde{r}_2, ..., \tilde{r}_i, ..., \tilde{r}_n)) = w'(\tilde{r}_1 + 2(r^* - \tilde{r}_1), ..., \tilde{r}_i + 2(r^* - \tilde{r}_i), ..., \tilde{r}_n + 2(r^* - \tilde{r}_n))$$

The Symmetriser criterion in here is again the concept that is the most similar to all of the concepts; however, in this time we would take just the real concepts (not imaginary ones) into account. In other words the RFSO would try to put the real concepts in front of each other.

Example2. Performing the subtractive clustering on the ten temporal observations presented in table 1, the value "15" is selected as the concerning cluster center. Based on this criterion, the observations are put against each other. In figure 5 it is illustrated how the concepts are symmetrised around this cluster center.

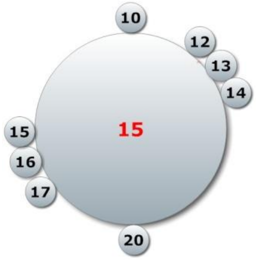

Fig. 5. Symmetrising the normal concepts of table 1 around the eighth observation

In figure 5, we have illustrated that the normal concepts can be symmetrised. This operator would let us discover the proper activities in order to return the smart home to the normal state.

Symmetrising the normal concepts we can provide a framework in which we can select the target in an adjustive manner. In other words, we can set the commands in a live attention to both system environment and actuation quality. Our recommendation to the future researchers who work on development in smart home is that we can put more complicated concepts such as activities in front of each other and may program a robot in order to perform the recovery activities. For example, we can put the heating action against the cooling action or the activity of "cleaning" and "washing" can be put against the activity of the "cooking" in order to return the home to the normal state. Again it should be mentioned that in here, we do not intend to verify a robotic-based assistance provision approach, and at the implementation phase, we would suffice to guide the smart home resident for realization of the recovery actions or activities.

B. Assistance provision process

The proposed assistance provision model relies on the learned symmetric concepts. At first, the normal world definition is taken by the reasoning system, then the criteria for distinguish of the normal from abnormal states are formed and finally, the possible recovery reactions or activities for the case of anomaly is surveyed and the best one is selected (see figure 6).

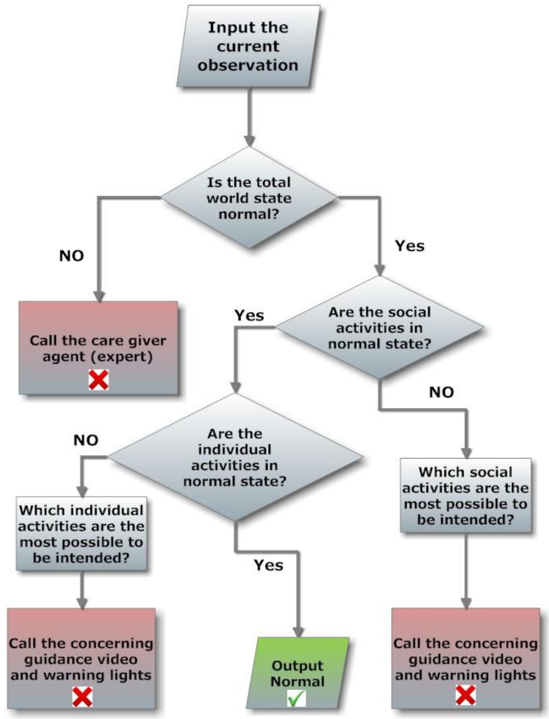

Fig. 6. Anomaly recognition and world actuation

One important point in assistance provision step is concerning to the discovery of the *mistaken half-realized intended* activity. In fact, applying the trained SVMs we can find the anomalies in a Boolean manner and the SVMs do not tell us in realization of what activity the anomaly is occurred. In order to discover the *intended uncompleted* activity, we would apply the activity functions in order to discover the most similar ongoing activity. We have already dealt with calculations of this function in [2], [9], [10]. In the following section, we would survey a case study in order to represent the practicality of the proposed approach.

V. Case Study – Anomaly Recognition and Assistance Provision in Smart Home

The information provided from activity recognition process is taken as the input of the anomaly recognition and assistance provision reasoning system. In [10], we have discussed how to calculate this knowledge in a data-driven manner. In this paper, in order to detect anomalies at the Normal World Generic Function (NWGF) level, the concerning fuzzy states are taken and the AFSO operator is performed on them. In table 2, we have presented a few samples of the fuzzy states and the AFSO operation result.

TABLE II. A FEW SAMPLES OF THE SVM TRAINING DATA

Cluster center number	Variable 1	Variable 2	Variable 3	Variable 4	Variable 5	Variable 6	Variable 8	Normal/Abnormal
1	0.083585679	0.0	0.09166985	0.098532928	0.0	0.0	0.080203962	1.0
2	0.083585679	0.0	0.09166985	0.098532928	0.0	0.0	0.080203962	1.0
3	0.083585679	0.0	0.09166985	0.098532928	0.0	0.0	0.080203962	1.0
4	0.91641432	1.0	0.90833015	0.90146707	1.0	1.0	0.91979604	0.0
5	0.91641432	1.0	0.90833015	0.90146707	1.0	1.0	0.91979604	0.0
6	0.91641432	1.0	0.90833015	0.90146707	1.0	1.0	0.91979604	0.0

In table 2, we can see that the NWGF is dependent on 8 role-playing variables. After normalization on the input data (the first three records), we have performed AFSO process on the input data. The last three records represent three samples of the result of the AFSO process on the first ones. In the next part, we would discuss the implementation of this system.

Because, in activity recognition step, per each influence range (IR), we can find different cluster centers, so we can find different criteria in order to symmetrise the learned concepts. In this section, we propose to symmetrise the concepts in the concepts' hierarchy level by level. In order to illustrate this job, we consider a circle per each concept and embed it by the circles representing its lower-level concepts. For example, considering the concept hierarchy proposed in case study of [10], we can draw a symmetric system that puts the concepts in front of each other. This concept hierarchy is demonstrated in figure 7. In [10], individual and simultaneous realizations of the three activities are observed and the models representing their realization patterns are formed. These activities are "hand washing", "studying" and "coffee making". In order to symmetrise the concepts represented in figure 7 (considering both normal and abnormal concepts), we applied the AFSO operator and in figure 8, we can see a schema representing the symmetrised concepts.

Fig. 7. Hierarchy of concepts in smart home [10]

In fact, per each concept of figure 7 we can configure an SVM classifier in order to detect the concerning anomalies of that concept. At each level, if no SVM classifier outputs normal state (no concept is well realized), then it can be inferred that in that level there is an anomaly.

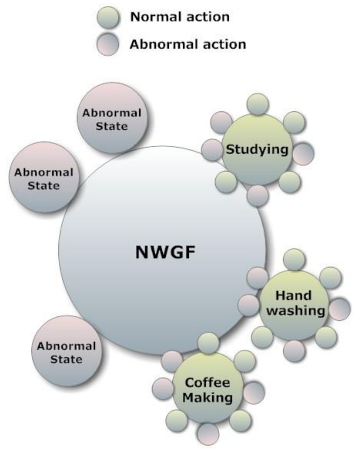

Fig. 8. Symmetrising the concepts around the cluster centers

In order to find precisely the *unrealized intended concept* we would find the most similar scenario applying the activity's formulas presented in [10]. Finally, according to the inferred similarity degrees, the proper guidance video or alarm is selected to be actuated.

A. Implementation

An SVM classifier is applied in order to be trained with both normal and abnormal world fuzzy states. In table 2, we have demonstrated a few (normalized) training data of the SVM classifier, which will be used to reason if the world state is normal or not. After that the SVM is trained with the entire fuzzy cluster centers and their symmetric values, it can be applied in order to reason in the world state normality and see if generally the world state is normal.

If per each concept (each circle in figure 8) an SVM be assigned, then we can reason in the correct realization of each activity too. In other words, not only we can infer the normality of the world state, but also we can reason in the details of the anomaly.

In LIARA [11], we benefit from the warning lights, speakers and a TV, which may become active in order to assist and guide the smart home resident. Therefore, by finding the anomaly type, we can give the proper assistance and guide to the resident who may forget accomplishment of actions.

For implementing and structuring the described Support Vector machines, we benefited from MATLAB [7] software and applying the "svmtrain" command an SVM structre is formed and it was trained with the both normal cluster centers of the activities and their symmetric values (as abnormal world states). The structure of the created SVM (for recognition of the general world state normality) is reported as the following:

```
      SupportVectors: [2x7 double]
               Alpha: [2x1 double]
                Bias: 2.9837e-016
      KernelFunction: @linear_kernel
  KernelFunctionArgs: {}
          GroupNames: [306x1 double]
SupportVectorIndices: [2x1 double]
           ScaleData: [1x1 struct]
       FigureHandles: []
```

In figure 9, we have illustrated a plot of the SVM classification, which indicates the relation of two variables to the normal and abnormal states:

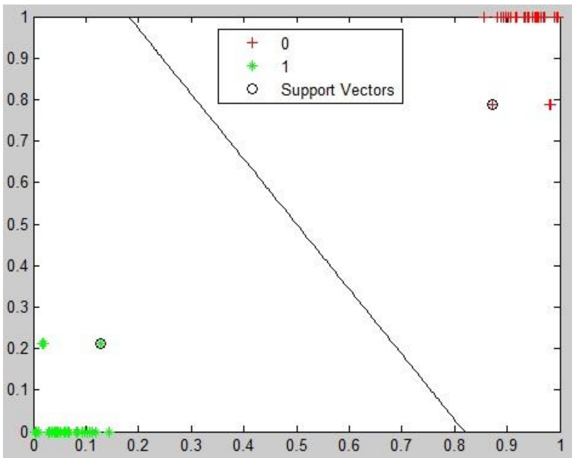

Fig. 9. Support vector for distinguish of normal from abnormal states

In figure 9, we can see two normal and abnormal world states are well isolated and distinguishable. In the consequence, in order to test the structured SVM for recognition objectives, we applied the "svmclassify" command in order to measure its ability in distinguish of the normal and abnormal states.

B. Validation and experimental results

In order to verify the consistency and coordination power of the calculated fuzzy conceptual structure with the real world, we tested it with *nine* correct scenario realizations (three times "coffee making" realizations, once "studying", once "hand washing" and four social combinations of the individual activities. Moreover, with an erroneous "coffee making" activity realization it was tested.

The reasoning system (which detects general anomalies) confirmed all of the nine correct realizations of the activities, but the erroneous realization of the "coffee making" activity was recognized as a part of normal world. The reason that we were unable to recognize the mentioned anomaly is that the SVM concerning to the general anomaly recognizer is trained with centers of the relatively big clusters; therefore, the partial mistake in an activity realization (forgetfulness of sugar) will not be recognizable in this level, and so it is not necessary to call the care-giver; in the consequence, this error in activity realization was recognized by the SVM assigned to the individual activities level.

Among individual activity models the activity of "coffee making" was selected as most possible (similar) *uncompleted intended* activity. In the consequence, the concerning actuators (video tape and warning lights) of this activity are called.

VI. CONCLUSION AND FUTURE RESEARCHES

An innovative data-driven fuzzy logic based approach for recognition of anomalies from temporal data is proposed. Not only the anomalies are recognizable, but also we can discover precisely where the problem is. In assistance provision section, we discussed how to data-drivenly infer the needed activity which recovers the world state to the normal state and even we discussed how this goal may be achieved in a data-driven manner.

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